

A model for the emergence of social organization in primates

M. N. Kuperman

*Consejo Nacional de Investigaciones Científicas y Técnicas
Centro Atómico Bariloche and Instituto Balseiro, 8400 Bariloche, Río Negro, Argentina
kuperman@cab.cnea.gov.ar*

Recent studies have established an apparent relationship between the repertoire of signals used for communication and neocortex size of different species of primates and the topology of the social network formed by the interactions between individuals. Inspired by these results, we have developed a model that qualitatively reproduces these observations. The model presents the social organization as a self organized processes where the size of the repertoire in one case and of the neocortex in another play a highly relevant role.

Keywords: Social systems; Networks; Self organization.

1. Introduction

The social organization of animal societies exhibits a great diversity of structures ranging from simple aggregates to complicated, hierarchical structures. The most complex organization is reflected in societies in which there are multiple roles, specialization, and even a division of labor. How these alternative structures arise, and why, remains poorly understood. A long-standing hypothesis is that complexity at the organizational level depends on complexity of signaling dynamics at the individual level—it has been argued, for example, that human language played a critical role in the emergence of human cultural complexity by fundamentally changing how information can be transmitted from individual to individual and intergenerationally [1]. This hypothesis assumes that semantic richness drives complexity at higher levels. Yet we also observe variation in complexity across animal societies [2, 3, 4] with little semantic richness. The signaling systems present in these societies are relatively simple with, for example, an average of approximately 16 signals and a maximum of 38 (considering all signals including those not used in the context of social bonding) in the 42 primate species for which data have been compiled [3]. The variation in these societies occurs at the individual level in appropriate contextual usage, signal form, signal repertoire size, and signaling frequency [5, 6, 7, 8, 9]. This variability, which results from individual differences in cognition, learning, social experience, is amplified by the presence of individuals at many different developmental stages.

On the other hand, some works suggest that the evolution of sociality drives the evolution of communicative complexity [10, 11, 12]. Although both of these

hypotheses are to some extent supported by comparative and experimental data [2, 3, 5, 13], and it seems likely that communicative and social complexity co-evolve, the relationship between the two remains poorly understood and has yet to be formally modelled.

Evolutionary increases in size of vocal repertoire were associated with an increment in group size (mammals in general [3, 14], see Fig 1. for non humans primate species) and time spend grooming [3]. At the same time various measures of brain size have been positively correlated with repertoire's size, as well as feeding innovation, learning and tool use in birds and primates, social complexity in birds, primates, carnivores, and some insectivores, dietary complexity in primates and unpredictability of environments in hominid, see [15] and references therein. Furthermore, the interplay between relative neocortex size and social organization has been established and discussed in many works [16, 17, 18, 19, 20, 21, 22].

Based on the ideas discussed above, in this work we explore the dynamics of an evolving social network composed of interacting individuals. Previous to a detailed explanation of the model we will make a brief description of the dynamical process. We consider a population of individuals whose social interaction is well represented by a network. Two individuals can interact only if they are socially linked though the social bound alone is not enough for a lasting interaction. In order to preserve the social bound the individuals must establish an effective communication, which not only will nourish and reinforce the existing link but also trigger new communication channels. If two linked individuals fail to communicate they may choose to break that bound and try to establish new links with more affine individuals.

The goal of this work is to explore how the ability to successfully communicate affects the construction of a social organization. Specifically we want to model how the effectiveness of the established communication affects the overall structure of this social organization, leading to fragmentation into smaller subgroups or isolation of some individuals. Topologically this translates into analyzing the size of connected components in the resulting social network by determining who interacts with whom.

The ability of the individuals to successfully communicate will be associated to two different but complementary characteristics of the population. Based on some of the results presented above, first we explore the resulting social organization considering populations with different signal repertoire sizes and we trace the correlation between group and repertoire sizes. Then, we propose associating the success of the communication to the relative neocortex size of the individuals, assuming that the probability of an effective communication will be proportional to the neocortex size. Once more, our assumptions are based on previous works that have established the links between social complexity, neocortical enlargement, and the size of social groupings. There are evolutionary [17, 23, 24, 25] and physiological [22, 26, 27] evidences that support the correlation between brain development and communication skills.

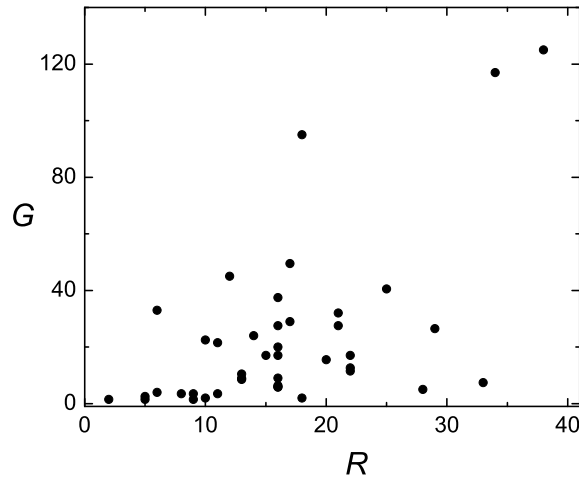


Fig. 1. Group size vs. repertory size among non humans primate species, from [3].

The model presented here is a generalization of a previous set of models exploring the causes of cultural diversity [28, 29, 30, 31, 32, 33]. In these models culture is defined as a set of individual attributes that are susceptible to social influence. The individuals, placed in the nodes of a network have attributes defined by a set of R features, each adopting one of q possible traits and represented by a vector profile of R components. The social dynamics is based on the premise the more alike an agent is to a neighbor, the more probably the agent will imitate one of the neighbor's traits [29]. The former is translated into a probability of interaction that is proportional to the number of common features shared by the individuals. The interaction is imitative, leading the two interacting individuals to the adoption of a common trait in one of the R cultural aspects previously not shared. At first sight this dynamics tends to homogenize the vector profile of neighboring agents to finally converge to a monocultural state, where all the individuals share the same vector profile [30, 31, 32, 33]. However, it has been shown that the system can remain frozen in a multicultural states with a number of different stable homogeneous or monocultural clusters. The number of clusters is a measure of cultural diversity of the steady final state.

We have adapted this model to study how variation in signal repertoire and neocortex size may affect the social organization in primates. In addition to the imitation dynamics analyzed in previous works, the present model considers an evolving network that on one side defines the interaction channels between individuals and on the other side is simultaneously being shaped by the distribution

of repertoires in the population. The network dynamics compete with the signaling dynamics by inhibiting the paths to a homogeneous state, thereby producing modular structures comprised of multiple connected components of individuals with identical signal repertoire profiles. The coevolution phenomenon produced by the feedback between the network topology and the individual profiles has not been studied before and is what defines the final social organization of the population.

We will analyze the effect of different repertoire and neocortex sizes on the communication between individuals through an abstract representation. Analogously to [28] the repertoire will be mimicked through a vector of size R . The vector represents the repertoire of the individuals. Each of the components of the vector will be associated to something that needs to be communicated and that with some abuse of notation we will call concept. On the other hand, the election that each individual makes to communicate a given concept must not necessarily be shared by the rest of the population, thus each of the components of the vector can adopt different values. Two individuals will interact only if they can communicate and this implies sharing a given number of pairs concept-signal in their respective repertoires. In terms of the model, that means that some of the values adopted by the same components in their respective signal vector must coincide. The interaction in turn promotes the imitation, generating a feedback process where a successful interaction promotes signaling imitation, while similar repertoire vectors enhance the interaction. As mentioned before, first we will consider populations with different vector sizes, i.e. different repertoire sizes. In a second approach we will not include the differences in repertoire sizes explicitly but we will assume that communication is more effective among individuals with bigger neocortex size [17, 22, 23, 25, 26]. The basis of this affirmation is associated to the fact that individuals with bigger brains develop stronger communicative skills, with increased capability to interpret social signals [11, 24, 27, 34]. The probability of interaction will still be proportional to the similarity between the vector profiles but the effectiveness of the communication between two individuals will be modulated by different functional forms encoding the information about the neocortex size.

2. The Model

The model considers a network of interacting individuals, initially connected through links to $2k$ neighbors. Each individual i is characterized by a repertoire profile, represented by a vector \vec{p}_i of R components or aspects (repertoire size). Each of the components of the repertoire is associated to a concept or fact that needs to be communicated. The communication operates via signaling. The richness and variety of the used signals are associated to the values adopted by each aspect (component) of the vector, that are discrete values ranging between 1 and q (number of traits). The use of numbers is only a convention inasmuch they act only as flags or labels. The repertoire profile is thus defined by the set of R values in the components of the vector \vec{p}_i . Initially, the values adopted by each of the components

of $\vec{\rho}_i$ are randomly assigned.

As mentioned in the introduction, the interaction between the individuals affects both the topology of the network and the distribution of the repertoire profiles. On one side, we adopt an imitation dynamics as a representation of the interaction that occurs between the individuals in a population that, by favoring the local convergence, drives the system to a uniform state with all the individuals sharing the same repertoire profile. On the other side, we include a dynamics that affects the network topology and tends to freeze local inhomogeneities that may arise by breaking links between individuals with different enough profiles. The competition between both effects leads the system to a self organized structure with separated groups or communities, each one comprising individuals sharing the same repertoire profile. A detailed explanation of both dynamics is included below.

2.1. Repertoire evolution

Two randomly chosen individuals connected by a link may interact between them with a probability σ associated to the similarity between their respective repertoire profiles [28]. Before describing the nature of the interaction, we explain how we measure the probability of it to occur.

The similarity between two profiles is measured through the distance between them. In this work we present the results obtained when considering the Hamming distance. Other metrics have been tested producing qualitatively the same results. The Hamming distance can be calculated as follows [36]. Consider two individuals i and j , with $\vec{\rho}_i$ and $\vec{\rho}_j$ their respective repertoire profiles. Each of the R components of the repertoire profile is characterized by a value ρ_i^k and ρ_j^k respectively, where k is the vector component index. After counting the number of coincidences, i.e. $\rho_i^k = \rho_j^k$ we obtain the Hamming distance $d_h(i, j)$ as $(R - \text{number of coincidences})$. In turn, we need to define the probability of interaction σ as a function of the distance.

$$\sigma = 1 - \frac{d_h}{R}. \quad (1)$$

Once defined the probability of interaction, we proceed to describe how the interaction between two individuals i and j affects their repertoire profiles. When the interaction is effective one of the features ρ_k^i such that $\rho_k^i \neq \rho_k^j$ is set equal to ρ_k^j . That is, the individual i imitates or adopts a repertoire value already adopted by j in a randomly chosen aspect. The roles of imitator-imitated are also randomly assigned to the pair i - j . Though it is evident that the interaction tends to reduce the distance between $\vec{\rho}_i$ and $\vec{\rho}_j$ it may affect the distances between i and the rest of the neighborhood as well. First we will consider that the communicational skills of a population are characterized by the size of the vector profiles.

In a second version of our model we will fix the vector size and modify Eq.(1) as follows

$$\sigma = 1 - \left(\frac{d_h}{R} \right)^{-\chi} \quad (2)$$

where χ is a parameter in the interval $(0,1)$ whose decrease is associated to an increase in the effectiveness of communication. We assume that this is an indirect measure of the effect of the neocortex size. The net effect is that a bigger neocortex will facilitate the communication and interaction between individuals. This fact is reflected in that the probability of interaction has lower thresholds values for lower values of χ , i.e larger neocortex.

2.2. Network evolution

As mentioned above, initially the individuals are located in a regular ordered network, with $2k$ neighbors [35]. Though the repertoire evolution favors the local convergence to a uniform state, the initial disordered distribution of the repertoire profiles can lead to a situation when the distance between the vector of a chosen subject and one of its neighbors is greater than the distance between the vector of the subject and that of another not neighboring one. If such is the case, the chosen subject may prefer including the more similar or affine individual into its neighborhood even at the cost of breaking an already established but non interesting link (we preserve the total number of links). This translates into the fact that links between non similar individuals can be broken to allow the creation of links between non connected similar individuals.

Applying the ideas discussed above, the network evolution acts in the following way. We choose a couple of linked individuals i and j , and a third one k not linked to i . We measure the distances between the repertoire vectors $d(i, k)$ and $d(i, j)$. If $d(i, k) < d(i, j)$ then the link between i and j is broken while a new link between i and k is established.

It is possible to understand now the competition between the convergence and segregation, associated to repertoire and network dynamics respectively. In our model, both dynamics act on the system in alternate turns. We define as t_r the time length of the repertoire dynamics turn and as t_n the corresponding to that of the network dynamics. This means that we first consider $N \times t_r$ pair interactions, with eventual changes in the repertoire, followed by $N \times t_n$ proposals of changes to the topology of the network. Some of the proposed changes in the repertoire vector and in the topology will be rejected according to the defined dynamics. The values t_r and t_n will play a determinant role on the dynamics of the system, as will be shown later.

3. Results

In the following section we describe the numerical results obtained when considering networks of 10^2 and 10^3 individuals and $k = 2$, without losing generality.

3.1. Variable vector size

The starting network is a regular ordered one. Initially, each individual is assigned a random repertoire vector \vec{p}_i of dimension $2 \leq R \leq 20$. The repertoire vector takes into account the several possibilities for referring a given object or activity that can be signaling in the community. Each component of the vector can adopt any integer number between 1 and q . In the following calculations $10 \leq q \leq 50$.

Throughout the calculations we use asynchronous update. The simulation proceeds in the following way. Once chosen the set of parameters R, q we need to choose the values t_r and t_n . The choice of these values will dictate the behavior of the system that will range from detailed segregation into small groups or convergence to a connected homogeneous population. When considering the repertoire evolution each evolution unit step consists in both cases in N interactions of a randomly chosen individual and a randomly chosen neighbor. On the other hand, when we consider the network evolution a third randomly chosen non neighboring individual is also picked up. Throughout the simulations we have taken $1 \leq t_n \leq 100$ and $0.1 \leq t_r \leq 10$. The characteristic time for repertoire adjustment must be shorter than that of network reconfiguration to avoid stimulating a segregation process that will end in a network composed by isolated and non interacting small groups.

We consider that the system has reached a stationary state when the number of changes of any nature, vector profile or network topology, goes to zero.

Plotted in Fig. 2-*a* we observe G , the group size versus R , with q varying between 10 and 50. The results for each value of R is averaged over 500 realizations. As can be seen in the figures displaying examples of final topologies, Fig. 2-*b*, individuals sharing the same profile tend to aggregate conforming communities within the population. The figures correspond to only one realization for $q = 50$ and $R = 2, 5, 15$ and 20 respectively. In these cases $t_r = 0.1$, $t_n = 10$

When we consider lower values of t_n we observe that the behavior of the number of groups is similar to the one displayed in Fig. 1, but showing a higher degree of segregation for lower values of R . The segregation of the network is due to the fact that in the last case we have let the convergence behavior act less time on the system between two consecutive changes in the topology produced by the network dynamics. If $t_r \leq 1$ then the network is fragmented into small groups for any of the values of R . On the contrary, if we increase the value of t_r we observe a rather robust behavior of the system with similar final topologies. The reverse is true when changing the values of t_n . This is due to the competition of two dynamics with opposite effects. On one side, the repertoire dynamics based on imitation drives the system to a homogeneous state. On the other side, the network dynamics tends to segregate the network and inhibit the convergence to uniformity. As an example, we show in Fig. 3 a typical outcome of individual realizations with $R = q = 20$, and different combinations of t_r and t_n .

In the limiting case, for large values of t_n , we recover the already know results for a static network [30, 33, 38]. In this case, the disorder of the underlying network

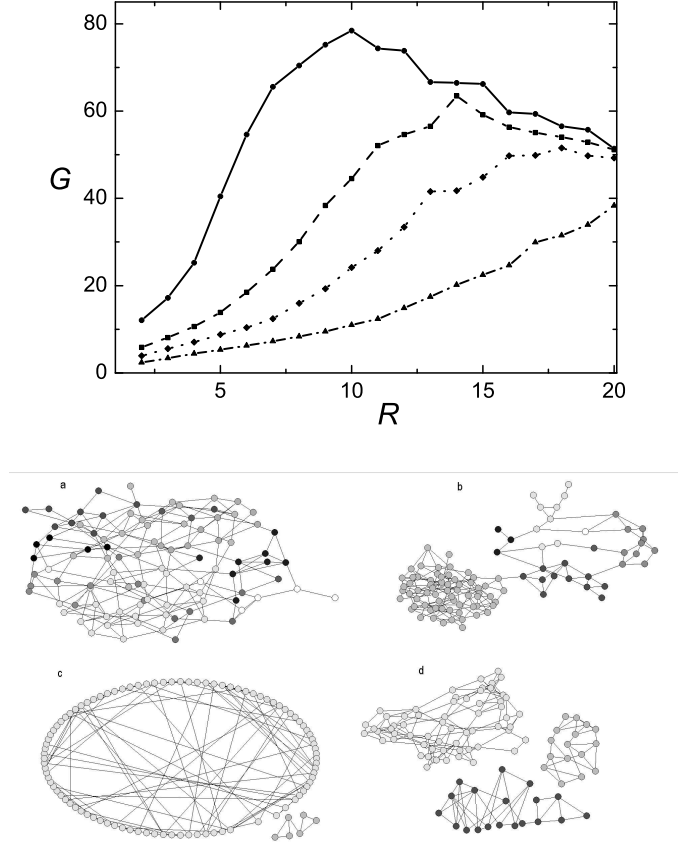
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Fig. 2. *a)* Group size vs. R for different values of the vector size: $q = 10$ (triangle), $q = 20$ (diamond), $q = 30$ (square), $q = 50$ (circle). *b)* Final configurations of networks with variable vector size. The results correspond to $q = 50, t_r = 0.1, t_n = 10$ and *a)* $R = 2$, *b)* $R = 5$; *c)* $R = 15$, *d)* $R = 20$

promotes the convergence to a homogeneous state whereas the increase of the ratio q/R facilitates the heterogeneity.

3.2. Fixed vector size

Throughout the realizations discussed in this section, we have considered a fixed R value, $R = 20$. The net effect of a more efficient communication is the convergence to more homogeneous final configurations. The size of the groups increases as χ diminishes. Figure 4 shows the values of G as a function of $r = 1/\chi$, for different values of q . It is clear that the group size suddenly increases when crossing a given

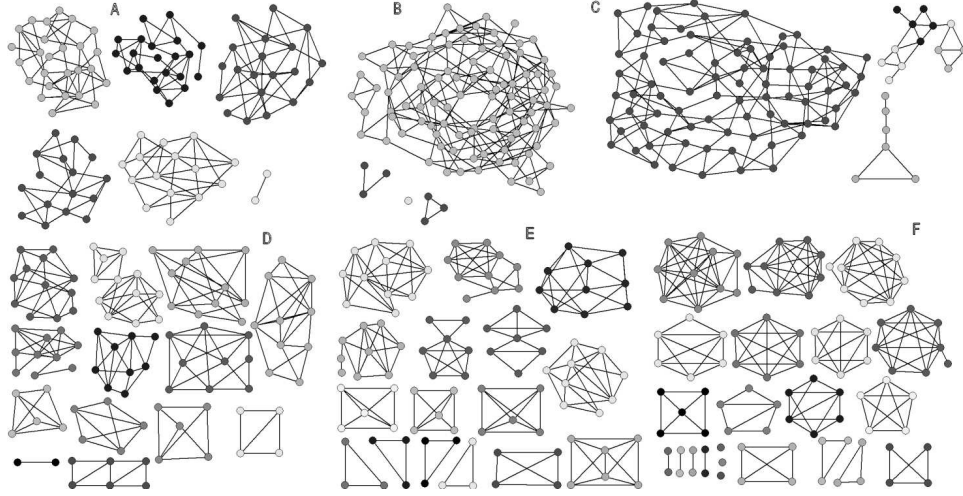


Fig. 3. Final configurations of networks. The results correspond to $q = 50$, $R = 10$, and (a) $t_r = 0.1$, $t_n = 1$, (b) $t_r = 0.1$, $t_n = 10$, (c) $t_r = 0.1$, $t_n = 100$, (d) $t_r = 1$, $t_n = 1$, (e) $t_r = 1$, $t_n = 10$, (f) $t_r = 1$, $t_n = 100$

value of χ , i. e., when the interaction between individuals is more probable, corresponding to $r \approx 2.5$. The most notable difference with respect to the case previously discussed is that the increment in group size is maintained. As it is clearly seen in Fig. 2-a, the former case showed that the group size non monotonic behaviour.

3.3. Conclusions

It has been nicely argued in [37] that cooperation is a fundamental aspect of *all* biological system. In their paper, they found that a *very simple and intuitive rule* is a good approximation for all the stationary social structures analyzed. In the present work, we argued that in social signaling systems the emerging structure is the result of the coevolution of the repertoire and the interaction between the elements of the system. The repertoire evolution can be thought as the lower level of cooperation evolution since, in any system, for elements to cooperate it should exist previously certain rules or information that are understandable for all of them. Our results, based on simple, but realistic, assumption of imitation and reconnection to similar element of the system shows clearly that the experimentally observed features in structured social behavior can be understood following these basic rules. Also we explore another biological aspect explicitly in our model, that is the relation between the size of the social group and the cognitive abilities of a given species. In doing that we make the connection between the size of a given repertoire size, the structure of a given social network (through the group size) and the cognitive abilities of the elements that belong to it. As discussed in [14], the interplay between neocortex

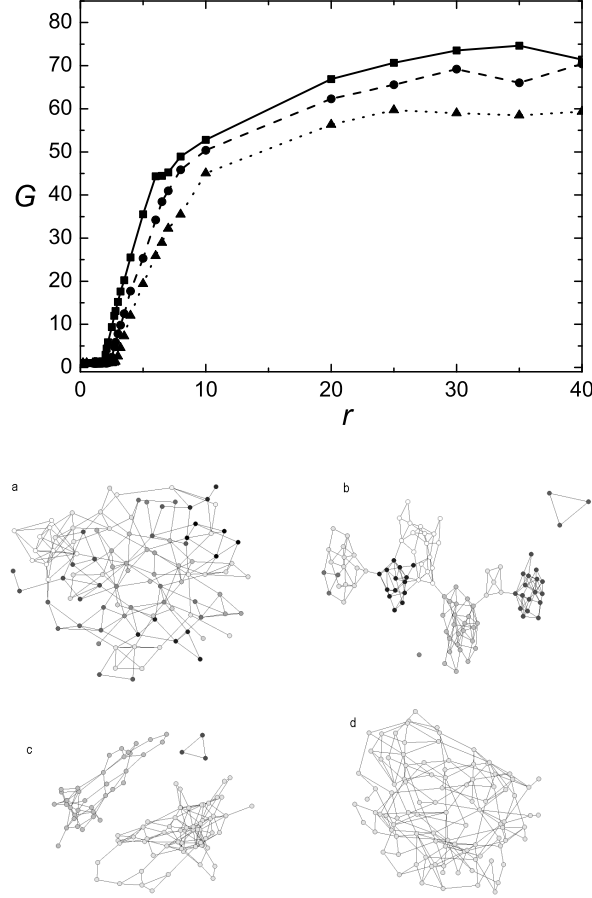


Fig. 4. *a*) Number of group G vs. $r = \frac{1}{\chi}$ for different values of q ; $q = 10$ (triangle), $q = 20$ (circle) $q = 40$ (square). *b*) Final network configurations for $q = 20$ and (a) $r = 2$, (b) $r = 5$, (c) $r = 10$, (d) $r = 25$.

size and group size is that coalitions allows animals to minimize the costs of living in groups. By coalitions, we understand the organization of a big population into smaller subgroups. As the cost of diary activities, like travel cost or the increasing of day journey, increase in groups of primates, they can manage, via coalition, to decrease such a negative affect of grouping. In this context, our results shows that the conformation of smaller units in a population is the results of a fast evolution of affinity in the shared information, and that can be linked at the same time with the capacities of compute it.

A fascinating aspect of this research is the connection with the evolution of intelligence. Why intelligence evolve? or in other words: How the ability to process information in a useful way evolve? Our simple model is not a answer for that, but it has some ingredients that are close to the social intelligence hypothesis which state that intelligence evolve not to solve physical problems but to process and use social information, such as understanding the existing alliances and use this information for deception [34, 39, 40].

The detailed entanglement of the set of signals that a social system can process and the topology of the structure that the described process generates are beyond the scope of this work. We think that this hardly explored region of knowledge can bring some light for understanding the fundamentals rules of social and biological systems which can be uses as innovating tools for practical issues in our social environments.

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